Trust and Doubt Terms in Financial Tweets and Periodic Reports

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Abstract

In this paper we present a study on expressions of trust and doubt in financial tweets and official periodic reports of companies. We use the trust and doubt wordlists that we created and analyze the presence of trust and doubt terms in both textual collections after some domain-specific text processing. In tweets, we have found that doubt is more frequently expressed than trust and forms higher peaks. Next, we have analyzed the relation between the filing dates of reports and the peaks in financial tweets with regard to their overall volume, trust tweets volume and doubt tweets volume. The analysis indicates that the Twitter community reacts more often to the quarterly than yearly reports and that the peaks are usually at the day of report, not before or after. As a result of corresponding analysis of textual content in annual reports, we present the frequencies of different trust/doubt terms in these reports and indicate some notable differences among their use by different companies.

Keywords: trust, doubt, tweets, periodic reports, wordlists

1. Introduction

Given the popularity of on-line social networking platforms, such as Twitter or Facebook, there has been a growing body of literature focused on analyzing social media content and its relation to various economic, political and social issues. For example, studies have analyzed the relationship between the Twitter data and financial indicators (Bollen et al., 2011; Smailović et al., 2014; Sprenger et al., 2014; Ranco et al., 2015; Gabrovšek et al., 2017), voting results (Tumasjan et al., 2010; Borondo et al., 2012; Eom et al., 2015; Grčar et al., 2017), crime (Gerber, 2014) or public health (Paul and Dredze, 2011). Other studies have focused on more formal documents (companies' reports) that have been analyzed in relation to various phenomena, such as company's financial performance (Qiu et al., 2006; Hajek et al., 2014), the cost of capital (Kothari et al., 2009), or fraud detection (Goel and Uzuner, 2016). Interestingly, compared to numerous applications of sentiment analysis, the aspect of trust is not a very common phenomenon to study in financial texts, although it is an important component of business.

In social networks, trust can be assessed from different aspects: from analyzing which users trust each other (Adali et al., 2010), to estimating trustworthiness of posted information (Zhao et al., 2016), and measuring expressed trust regarding an entity mentioned in a post. In addition, the methods for assessing trust are diverse: one can analyze the network structure, interactions between users, or examine content of posts. Sherchan et al. (2013) discuss definitions, aspects, properties and models of trust, and provide a survey of trust in social networks. They categorize sources of information regarding trust into attitudes, behaviours and experiences, while methods for calculating trust are grouped into network-based, interaction-based and hybrid ones.

Also periodic reporting has become an appealing topic of research. The main goal of financial reporting is to ensure high quality, useful information about the financial position of firms, their performance and changes (IASB, 2015) to a wide range of users (e.g. investors, financial institutions, employees, the government). Firms publish annual (and other periodical) reports, in which they—as summarised by Fuoli (2017) —construct and promote positive corporate image and gain trust. Related research focuses on various aspects, including the devices used to create an ethical image in corporate social responsibility (CSR) reports (Aiezza, 2015), impression management in chairman's statements (Merkl Davies et al., 2011), differences in stance expressions (strongly related to trust building) between annual reports and CSR reports (Fuoli, 2017). El-Haj et al. (2016) focus only on performance sentences (in the UK Preliminary Earning Announcements) on which they also test machine-learning methods for their identification, as well as for identifying the expressed attribution (internal or external factor related to the expressed performance) and tone.

In our paper, we focus on explicit mentions of trust and doubt terms in financial communications. In a preliminary study of correlations between linguistic characteristics and financial performance of companies, limited to only four firms (Smailović et al., 2017), we have used the trust and doubt wordlist for the first time, and the analysis showed that doubt terms are correlated to the financial indicators of failure (interestingly, more than the words from more frequently used lexicons of positive and negative words). For this reason, in our paper we further explore the expression of trust and doubt in financial communication. We are particularly interested in trust and doubt terms in Twitter posts (tweets) and periodic reports, and in observing the reaction to the periodic reports on Twitter. We focus on companies from the Dow Jones Industrial Average 30 (DJIA) index in a two-year period (2014-2015).

After introducing the manually created trust and doubt wordlists (Section 2.), we describe a lexicon-based approach for assigning the tweets into the two categories (trust and doubt) (Section 3.1.) and analyze the reactions to periodic reports in Twitter (through the peaks in the volume of all tweets, trust tweets or doubt tweets). In Section 3.2., we focus on trust and doubt terms in annual reports and, based-on a frequency analysis, report on some differences in the usage of trust and doubt terms between different companies. Finally, we conclude the paper and present the future research steps.

2. Trust/Doubt Wordlists

The wordlists used in this paper contain manually collected (near) synonyms of words *trust* and *doubt* from WordNet (Fellbaum, 1998; Miller, 1995)[1] and online dictionaries[2]. In the current version (v1.1), we included 25 terms for trust and 77 terms for doubt. The wordlists are publicly available at `http://kt.ijs.si/data/trust_doubt_wl.zip`.

A selection of trust/doubt terms from the wordlists is shown in Figure 1. The part of speech (POS) of each term is specified in parentheses (*n*-noun, *v*-verb, *adj*-adjective), while the # sign denotes that a term is in its derived form.

Trust	Doubt
assurance(n)	disbelief(n)
#assurances(n)	#disbeliefs(n)
confidence(n)	disenchantment(n)
confident(adj)	disillusion(n)
credence(n)	disillusionment(n)
faith(n)	distrust(n)
faithful(adj)	distrust(v)
reliable(adj)	#distrusted(v)
reliance(n)	distrustful(adj)
reliant(adj)	distrustfulness(n)
…	…

Figure 1: A selection of terms from the trust and doubt wordlists.

The wordlists have been used for the first time in our preliminary study of reports of four companies (Smailović et al., 2017), where we have shown the correlation between the doubt terms and financial performance. In the current version, some new terms were added (and some mistakes removed)[3]. We also describe here the resource in more detail and use it on other datasets and for other purposes.

The resource the most similar to ours is a list of 30 trust and distrust related words, presented in the study of (Jian et al., 2000). The authors study terms used for expressing three types of trust (trust towards machines, towards humans and trust in general). In future, we will investigate if the terms are useful for extending our wordlists.

If based on our wordlists, one wanted to create the trust and doubt wordlists for another language, lexical resources with linked senses over different languages could be considered (e.g. BabelNet[4] or Multilingual WordNet[5]).

3. Wordlist-based study of Trust and Doubt in Financial Communication

We use the trust/doubt wordlists that are described in Section 2. for conducting a wordlist-based study on two types of text: (i) tweets, which discuss the DJIA 30 companies in the years 2014 and 2015, and (ii) the corresponding annual reports of the companies.

3.1. Tweets

We analysed the presence of trust and doubt terms in tweets about the 30 DJIA companies over a two-year period. The data was acquired by the Twitter Search API, where a query is specified by the stock cashtag. A cashtag is a word with the dollar sign as the first character. Cashtags with stock ticker symbols (short codes that represent specific stocks) are used in Twitter messages to refer to particular stocks or companies (e.g., "$MSFT" for Microsoft). We collected 5,570,817 tweets in the period from January 1, 2014 until December 31, 2015.

Lexicons have been frequently used as a resource for sentiment analysis, where documents (e.g. tweets) are assigned to positive or negative class based on the frequencies of words from the positive or negative wordlists (Loughran and McDonald, 2016). In our case, we use the lexicon-based approach to classify the tweets in the categories of trust and doubt. The initial approach for categorizing tweets as expressing trust and/or doubt is straight-forward: for each tweet, the trust value of a company-day combination is increased by 1, if at least one trust term from the trust wordlist is matched.[6] The same is repeated for each tweet for the doubt terms. This results (for each tweet) in the increase of 1 for trust, doubt, none or both values for the company-day. The aggregated results for all DJIA 30 companies are presented in Figure 2, where we display tweet volume, trust and doubt over time. As it can be seen from the figure, there are several peaks in doubt and a substantial increase in trust over several months in the year 2015.

Content analysis of the tweets revealed that there is a need for handling two important aspects, which were not taken into account by our basic approach for assessing trust and doubt. First, there is a need for handling negated trust/doubt terms, and second, we noticed that the word "trust" is used not only related to, e.g., *reliability* and *confidence*, but often also in the context of mentioning investment funds. We did not find the ambiguity of any of the other considered terms so prominent.

In order to handle negations, we checked if there is a negation word (e.g., *no*, *not*, *isn't*, *aren't*, *wasn't*, etc., but also grammatically incorrect forms such as *dont*, *didnt*, *wont*,

[1] `http://wordnet.princeton.edu`

[2] E.g., `http://thesaurus.yourdictionary.com/doubt`

[3] We added more than 10 new terms and corrected some minor mistakes (some forms were marked as base forms, but were in fact derived forms, we removed some duplicates etc.).

[4] `http://babelnet.org/`

[5] `http://globalwordnet.org/wordnets-in-the-world/`

[6] The approach for retrieving tweets based on trust/doubt terms uses unique terms from the trust/doubt wordlists, without taking into account their POS tags or information regarding their derived forms.

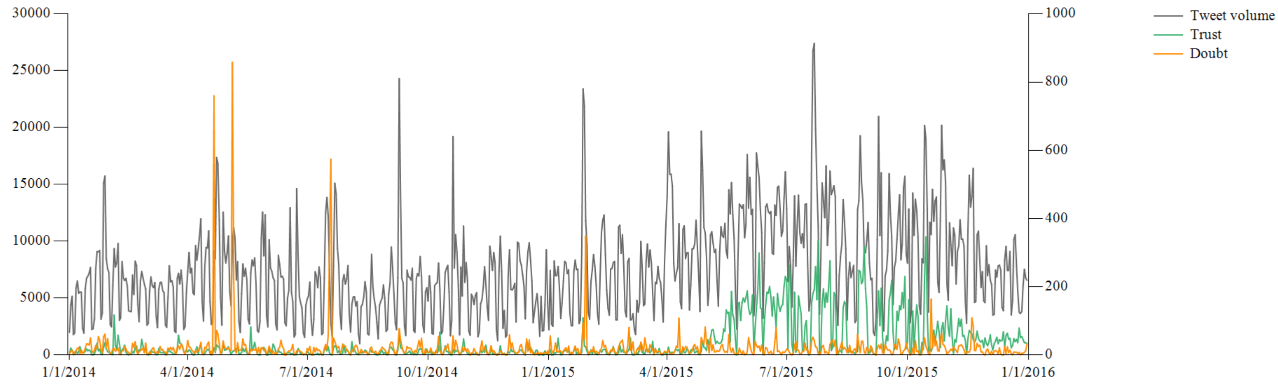

Figure 2: Tweet volume (gray, left y axis), trust (green, right y axis) and doubt (orange, right y axis) over time aggregated for all DJIA 30 companies (time labels have MM/DD/YYYY format).

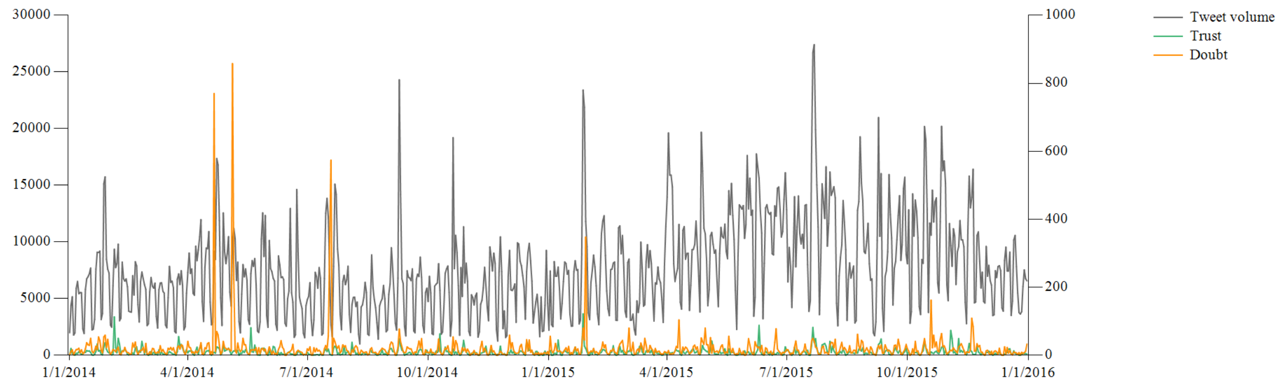

Figure 3: Tweet volume (gray, left y axis), trust (green, right y axis) and doubt (orange, right y axis) over time aggregated for all DJIA 30 companies (time labels have MM/DD/YYYY format). Both modifications of the methodology (handling negations and removing trust terms related to the investment funds) are taken into account.

etc.) immediately before the trust/doubt term under consideration. We treated such negated trust terms as doubt terms, and vice versa. This adjustment had only a small influence on the overall results: only 1.49% of the matched trust terms and 3.15% of doubt terms were found to be negated, which caused also only small changes in the visualization of the aggregated DJIA 30 results.

The second modification has, however, changed the results considerably. In this scenario, in order to avoid trust terms related to the context of investment funds, we did not take into account the word "Trust" if it appeared in the capitalized form, unless it was at the beginning of a tweet or positioned after a selection of punctuation marks ("."/"!"/"?"). By applying such an approach, we excluded 20,024 capitalized words "Trust" out of the 21,841 words *trust* (regardless of the capitalization) detected in the DJIA 30 tweets.

The aggregated results for DJIA 30 companies, after applying both modifications (handling negations and removing trust terms related to the investment funds) are shown in Figure 3. From the comparison with Figure 2, it can be seen that the increase in trust in the year 2015 vanished, which indicates that in that time period the Twitter community discussed investment funds. Several peaks of the doubt score remained and we made a more detailed analysis of the tweets which contributed to these peaks. The analysis revealed that high increases in doubt might be to some extent explained by retweets of certain Twitter posts, written by specific analysts or journals. Additionally, in Figure 5, we show an example of results for an individual company, i.e. the Apple company. The vertical red and blue lines mark the 10-K and 10-Q filing dates enabling one to observe if there exist tweet volume, trust or doubt changes around such dates.

3.1.1. Peaks and Trends in Tweet Volume, Trust and Doubt

After the analysis of Twitter posts from the perspective of trust and doubt expressions, we analysed the presence of such expressions near specific business-reporting events. We examined if there is a connection between changes in tweet volume, trust or doubt tweets, and the filing dates of the periodic reports. Specifically, we examined if there exist local peaks or trends in tweet volume/trust/doubt around the filing dates of 60 10-K and 180 10-Q reports of DJIA 30 companies in years 2014 and 2015. In this experiment, both adjustments of the methodology for assessing trust and doubt (handling negations and trust terms related to the investment funds) were applied.

The results are shown in Table 1, where we display percentages of reports that coincide with peaks in tweet vol-

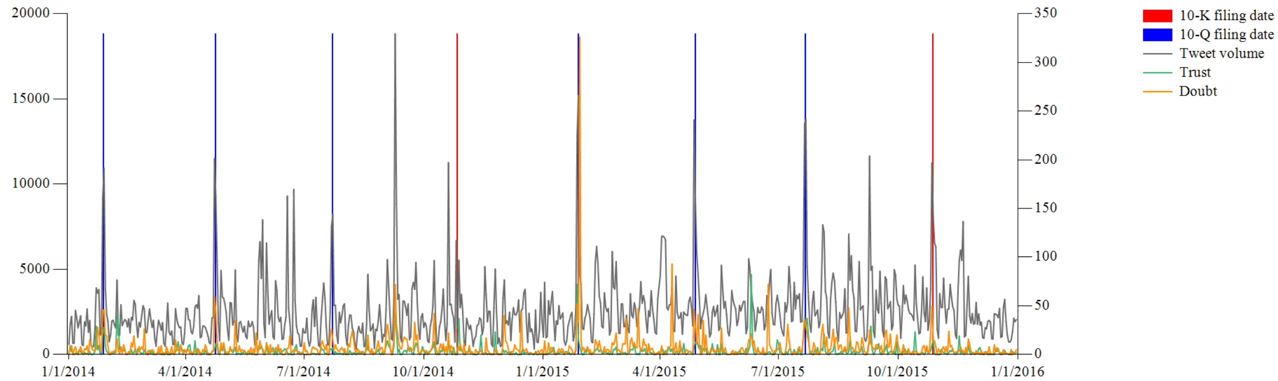

Figure 5: Tweet volume (gray, left y axis), trust (green, right y axis) and doubt (orange, right y axis) over time for the Apple company (time labels have MM/DD/YYYY format). The vertical red and blue lines mark the 10-K and 10-Q filing dates, respectively. Both modifications of the methodology (handling negations and trust terms related to the investment funds) are applied.

Random-All	Peak(-1)	Peak(0)	Peak(+1)	Inc. trend	Dec. trend
Volume	25.42%	27.92%	23.33%	17.92%	25.83%
Trust	7.50%	6.67%	7.08%	0.83%	1.25%
Doubt	10.00%	10.83%	7.50%	2.08%	1.25%
Report-All	Peak(-1)	Peak(0)	Peak(+1)	Inc. trend	Dec. trend
Volume	18.75%	44.17%	24.58%	15.00%	12.90%
Trust	9.58%	14.17%	10.83%	2.50%	2.50%
Doubt	12.08%	12.91%	11.67%	2.92%	2.50%
10-K	Peak(-1)	Peak(0)	Peak(+1)	Inc. trend	Dec. trend
Volume	23.33%	38.33%	18.33%	20.00%	23.30%
Trust	6.67%	8.33%	6.67%	0.00%	0.00%
Doubt	11.67%	16.67%	10.00%	0.00%	0.00%
10-Q	Peak(-1)	Peak(0)	Peak(+1)	Inc. trend	Dec. trend
Volume	17.78%	47.78%	27.22%	19.44%	13.89%
Trust	11.67%	16.67%	12.22%	3.33%	3.33%
Doubt	12.22%	12.78%	12.78%	5.00%	3.89%

Table 1: Percentages of random dates and filing dates of all reports, 10-K reports and 10-Q reports related to peaks and trends of tweet volume/trust/doubt around their filing dates. See Figure 4 for illustration of different types of peaks and trends.

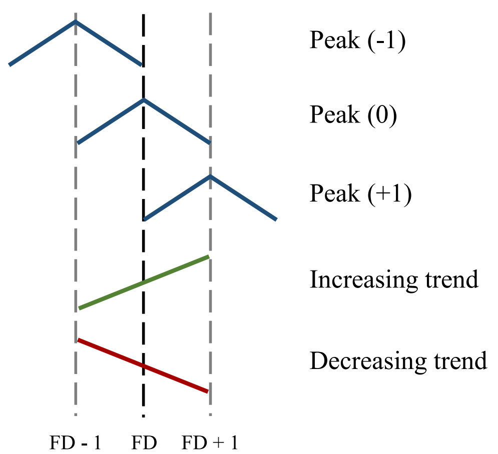

Figure 4: Illustration of changes and their labels in tweet volume, trust or doubt around a filing date (FD), 1 day preceding (FD-1) and following (FD+1) the filing date.

ume, trust and doubt on the exact day (Peak (0)), one day before (Peak (-1)), and one day after (Peak (+1)) filing the reports. Additionally, the table displays results of detecting increasing and decreasing trends in tweet volume/trust/doubt in a time period of 3 days around the filing dates (the filing date, and 1 day preceding and following the filing date). See Figure 4 for illustration of changes in tweet volume/trust/doubt and corresponding labels. Note that we did not apply thresholding or quantification, so for example a peak is equally detected given tweet frequencies (2,10,2) or (10,11,10) for three consecutive days.

The results in Table 1 are presented in terms of percentages of all reports, 10-K and 10-Q reports related to the described peaks and trends, while the first triplet of rows shows percentages for the same number of days as for all reports, but chosen at random dates. As it can be seen from the results, the largest percentage is observed in tweet volume on the exact day when the periodic reports are filed (and less on the preceding or the following day). This is ev-

Random-All	Peak(-1)	Peak(0)	Peak(+1)
Volume	-0.0046 (0.5043)	0.0047 (0.4954)	-0.0069 (0.3255)
Trust	-0.0048 (0.4967)	-0.0065 (0.3506)	-0.0013 (0.8514)
Doubt	-0.0023 (0.7412)	0.0040 (0.5652)	-0.0071 (0.3078)
Reports-All	**Peak(-1)**	**Peak(0)**	**Peak(+1)**
Volume	**-0.0153 (0.0285)**	**0.0495 (1.5e-12)**	-0.0005 (0.9438)
Trust	0.0092 (0.1899)	**0.0283 (5.3e-05)**	**0.0143 (0.0403)**
Doubt	0.0121 (0.0846)	**0.0152 (0.0298)**	0.0104 (0.1361)

Table 2: Correlation among the days with peaks of volume, trust and doubt and the reporting days. The values presented are Pearson correlation coefficients (and p-values) for tweet peaks and report dates (data was concatenated for all of the reports and studied companies). Significant results (p<0.05) are marked in bold.

ident also for both types of reports (10-K and 10-Q), however it seems that the Twitter community reacts more often to 10-Q than 10-K reports. Furthermore, it seems that the increasing and decreasing trends around the filing dates of periodic reports may be observed in tweet volume, but very rarely in trust or doubt.

For a comparison, we have also calculated the results for random dates (see top rows in Table 1). We took the same number of random dates as for the joint report dates (so the values of *Random-All* are directly comparable with the the *Report-All* values). We can notice that the reporting dates with peaks are higher in all the categories, with the exception of the peak volume on the preceding day (Peak(-1)). The largest difference (16.25%) is in the peak of volume on the reporting day. The results for trends are less consistent as they occur very rarely.

Next, to verify whether the peaks in volume, trust and doubt appear more often near report filing dates, we compared the actual dates and random dates with regard to their correlation with the peaks in the three phenomena of interest. Results of this analysis are presented in Table 2 and they suggest that there is a non-coincidental correlation among the report filing dates (Peak(0)) and the volume, trust and doubt peaks in tweets.

3.2. Annual Reports

Our analysis of trust and doubt terms appearance in tweets was mostly focused on behaviour during publishing dates of periodic reports, so we briefly analysed also the use of these terms in the reports. For this purpose we have collected the 10-K annual reports for the firms in DJIA 30. We selected the reports corresponding to the years of Twitter collection, i.e. the reports with filing dates in years 2014 and 2015. For the reports we have selected only the Part I, and Items 7 and 7A from Part II. These are less regulated textual parts of reports, allowing for more flexibility and expression of opinion.

We were interested in finding out, which terms from trust and doubt wordlists are more frequently used, and which companies use more of trust/doubt terms. For the list of terms from the trust and doubt wordlists, we have calculated the number of occurrences per firm and in total, including the relative and absolute frequencies.[7] The results of the absolute frequencies of trust and doubt terms joint for all companies are presented in Table 3 showing that the most used term from the Trust wordlist is *assurance*, followed by terms *confidence, trust* and *reliable*. For the terms from the Doubt wordlist, *uncertainty* takes the lead, while term *doubt* has only two occurences in the corpus.

To find out which firms use the largest amount of the trust and doubt terms, we calculated the relative frequencies of the trust and doubt terms (per 1000 words). The trust terms are the most frequently used in the reports of JPM (1.486 permille), followed by CAT, IBM and AAPL. Less than one permille of trust terms characterizes the reports of CVX and XOM, which are both from Oil and Gas industry.

The doubt terms are more frequent in the reports of TRV (0.832 permille), UNH, CSCO and AAPL, while interestingly, IBM and JPM together with WMT are the ones that express doubt (by using doubt terms) the least.

Trust terms	freq.	Doubt terms	freq.
assurance	331	uncertainty	603
confidence	134	question	25
trust	111	doubtful	19
reliable	68	suspicious	16
reliance	46	tentative	3
reliant	8	doubt	2
faith	2		
TOTAL	700	TOTAL	668

Table 3: Trust and doubt terms (lemmas) and their absolute frequencies in the corpus of cleaned annual reports.

4. Conclusion

The work presented in this paper discusses the expression of trust and doubt in financial tweets and periodic reports corresponding to companies from the DJIA 30 Index in years 2014 and 2015. We use a wordlist-based approach to categorize the tweets into trust and doubt categories and analyze them from the perspective of interactions between social media posts and selected business reporting events. We analyzed the relationship between changes in tweet volume, trust or doubt, and the filing dates of the annual and quarterly reports. Results show that the Twitter users react mostly on the same day a report is filed, which was further confirmed by a comparison with random dates. Finally, our results indicate that the increasing and decreasing trends

[7]For the lemmatization, we used the LemmaGen lemmatizer (Jursic et al., 2010).

around the filing dates may be observed in tweet volume, but almost never in expressions of trust or doubt.

For the annual reports we selected the parts, where management has more freedom to express their opinion, and calculated the frequencies of the words from the trust/doubt wordlists. We showed that the most used term from the trust list is *assurance*, possibly an ambiguous term, and the most used term from doubt terms is *uncertainty*. We have also analyzed which firms use the trust and doubt terms more than others, and showed that JPM and IBM are between the companies that use the trust terms the most and the doubt terms the least. In future work we will correlate the usage of trust and doubt terms with financial performance information and see if trust and doubt expressions are correlated with financial indicators on the dataset of companies of DJIA 30, which would confirm our findings from the preliminary study of the correlation between content of annual reports and firms' financial performance (Smailović et al., 2017), where doubt terms showed significant correlations. Moreover, we plan to focus on an in depth corpus analysis of the terms from the wordlists, and extract and analyze their collocations, change over time and their original textual context.

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